

## **HUMAN VARIABILITY, TASK COMPLEXITY AND MOTIVATION CONTRIBUTION IN MANUFACTURING**

Angel Sanchez, Shafizal Mat, Yee Mey Goh, Keith Case  
Mechanical and Manufacturing Engineering  
Loughborough University  
Loughborough  
Leicestershire, LE11 3TU, UK  
A.Sanchez@lboro.ac.uk, S.Mat@lboro.ac.uk  
Y.Goh@lboro.ac.uk, K.Case@lboro.ac.uk

### **ABSTRACT**

This paper is a preliminary study of the human contribution to variability in manufacturing industry and how motivation and learning play a key role in this contribution. The longer term aim is to incorporate this understanding in a methodology, using principles and guidelines, that aims to help in the design of intelligent automation that reduces product variability. This paper reports on the early stages that are concerned with understanding relationships between human-induced product variability, task complexity and human characteristics and capabilities. Two areas have been selected for initial study in manufacturing industry: (a) the relationship between manual task complexity and product variability and (b) the relationship between employee motivational factors and learning behaviours. The paper discusses the progress to date in conducting initial empirical studies and surveys in industry and draws tentative conclusions of the value of this knowledge to the overall objective of intelligent automation.

**Keywords:** Human variability, Motivation, Manufacturing Automation.

### **1 INTRODUCTION**

The UK manufacturing industry is the sixth largest in the world and it is a significant contributor to the UK's GDP (Gross Domestic Product). The UK Aerospace and Defence industry is the second in the world, accounting for \$40bn of annual sales and the UK has the third largest automotive industry in Europe, with total sales of around £9bn (11% of the UK's total exports) (Pricewaterhouse 2009). Humans play a key role in manufacturing processes and this role has been changing through the years due to advances in technology but also due to globalisation and social changes. Automation in manufacturing has replaced some dangerous, mundane, arduous and routine manual operations. For example, transportation of heavy parts, stamping large parts, repetitive welding and monotonous assembly processes are no longer performed by humans. In contrast, skilled operators carry out critical tasks in different industries such as aerospace, automobile, heavy-machinery and renewable energies, being an essential part of the production processes. Limited automation has been applied in high-value manufacturing companies because of the extremely skilled nature of the work embedded in the tasks. The mix of human factors such worker skills, experience and decision-making capability involved in these complex tasks plus the high-value parts being handled in the processes make these notably difficult to automate. Understanding how humans perform complex tasks will help to reduce variability in products/outputs, to design future processes and eventually, to achieve more appropriate automation solutions. Many manual operations, such as inspection, adjustment and rework do not add value to the final product, and hence it can be said that these operations are fruitless. If these operations can be eliminated from the production process, the productivity and competitiveness of UK industry will increase. Furthermore, employee motivational factors and learning behaviours are important contributors to product variability and thus will affect job satisfaction and turnover in manufacturing industry.

## 2 LITERATURE REVIEW

### Human Variability

In production management, variability is suggested as a main cause of lack of robustness in the production process. Some of the most common sources of variability are process equipment capabilities and calibration limits, raw materials, sampling variability, environmental factors and human factors within the plant facility (Glodek *et al.* 2006). In addition, other factors affecting human variability include social and organisational factors (Govindaraju, Pennathur and Mital 2001). All these factors can be grouped into three main sources of variability: Component, Process and Human. The aim of this research is limited to human variability although all three are highly linked and studying the human contribution to variability without inferences from components and processes is one of the biggest challenges to be faced in this study.

It is well known that in manufacturing environments humans can adapt and “readjust” to variation in materials and processes, making decisions according to these variations and consequently, perform tasks that otherwise would be impossible to be finished with the established time and quality standards. However, humans can also introduce variations in the process by the mere fact of being humans (Sandom and Harvey 2004).

Human variability in manufacturing can be described as the capability that humans have for performing the same task in different ways. This variability is found between different individuals with a range of internal and external factors. Internal factors are (among others): age, gender, race, culture, education, physical condition, tiredness, motivation, social factors and human relationships inside and outside the workplace. External factors are, for instance, environmental conditions (light, cold, noise) or constraints (time, space). These sets of factors will play a fundamental role in how a worker develops a specific task and it can result in a variability of performance and outputs during the work shift. This set of factors will also determine significant differences between operators working under the same conditions. It is claimed that variations in human task execution can be found even with the limitations and control imposed by job simplification and automation in modern manufacturing systems (Osman 2010). The influence of complex tasks on human behaviour and disparity of output has become of more interest in recent years. The more complex a task is the more likely dissimilar results will be obtained because it demands more attention and effort. More effort can also be required when the subject is fatigued or works under extreme environmental conditions (Backs and Boucsein 2000).

The nature of complex manual processes means that cognitive aspects related to decision making play a fundamental role in understanding human variability. Klein and Zsombok (1991) suggested that people use their past experiences to make better comparisons and decisions. They further argued that when the situation is familiar, the decision makers may never have to contemplate options (Klein, Calderwood and Clinton-Cirocco 1986). Based on this, novice decision makers could be taught to recognise typical cases, and to identify when cases were not typical, in order to supply a picture of the distribution of situations (Tversky, Kahneman, and Slovic 1982). Furthermore, the first option contemplated by experienced decision makers is usually acceptable. It was found that decision makers (chess players in this case study) can produce reasonable choices initially, using their experience to construct the option generation process (Klein *et al.* 1995). This option generation process occurs in an organised, not by chance, manner. A major conclusion of the study is that even moderately experienced people can generate feasible options.

Due to the complicated interactions of humans, processes and component variability, it is unclear when automation could be beneficial, i.e. in reducing variability caused by the operators during a manufacturing process. Therefore, understanding the human’s role in these processes will help to decide which tasks are suitable to automate and vice versa.

It can be seen that human variability is a complex problem. The aim of this research is try to understand which human attributes and what kind of situations or circumstances will be likely to introduce variability in complex tasks within the manufacturing process. If the precise reasons for variability can be identified and studied, it would be possible to eliminate them from the process by incorporating this knowledge in the design process.

## 2.1 Motivation and Learning Curves

Employee demotivation is related to job dissatisfaction and therefore changing job intention in many organisations. Some organisations motivate their employees by offering them rewards for satisfactory performance and for working more effectively towards their organisational goals (Elding *et al.* 2006). Several theoretical frameworks have been developed and used to explain the issue of employee motivation and job satisfaction. The concept of job motivation or employee motivation is broad and complex, and many scientists have agreed its basic characteristics and defined motivation as “the set of processes that arouse, direct and maintain human behaviours towards attaining goals” (Bent *et al.* 1999).

According to Ullah Khan *et al.* (2010) employees should motivate themselves to work hard to satisfy their personal goals as well as the organisational objectives. Therefore in this competitive world it is a challenge for the management to motivate them to offer very good services for customers. This aligns the individual personal goals to those of the organisational goals. Locke and Latham (1984) in their goal-setting model predict that employee motivation and performance will increase if they have clear goals. Many scholars suggest that employee motivation and vision is positively affected by organisational learning, while others found that organisational learning is positively affected by the vision and motivation of the employee.

There are many approaches to motivating employees, teams and organisations. Hitka (2011) mentioned that some of them are focused on rationality and orderliness, with for instance employees being required to do more difficult or complex tasks. In this very competitive business environment, one of the biggest challenges that managers face is the use of employee motivational techniques to achieve their business goals. It is suggested that the most influential tool to successful strategy execution is the proper design of reward structures that will motivate the employees (Thompson *et al.* 2005).

There is still debate on which rewards really motivate workers but money is not the main factor as Barrier (1996) suggested. He claimed that the stronger motivator of employee performance is showing appreciation rather than giving monetary incentives. Not only that, many practitioners agree that jobholders are more concerned about their recognition and job security compared to financial rewards. Jamalmohammadi *et al.* (2012) in their study on the relationship between employee motivational factors and efficiency concluded that for directing employee motivation in an organisation, managers should consider the fundamental nature of work as this will affect the success of employees more than other factors. Factors include an equal and fair reward system, work incentives, inspiration, promotion and career advancement, and also interaction between staff and environment leading to efficiency.

There have been many studies in industries such as automotive, aerospace, construction, electronic and software to measure employee performance in new and repetitive tasks. An efficient tool to monitor performance is learning curves (LC) theories. Wright (1936) proposed this theory to observe cost reduction due to repetitive tasks in production plants. There are several factors that will impact on the employees' learning process such as training program structure, employee motivation, experience and task complexity and these factors can be analysed using LC theories (Anzanello and Fogliatto 2011).

Guimaraes *et al.* (2012) applied the LC model to measure whether rotation of different task complexities will affect the employee learning rate and performance. The intervention was shown to reduce accidents in the workplace by 80%, reduce absenteeism by 45% and also eliminated work related to musculoskeletal disorders, medical conditions as well as increasing turnover. The output rate of the multifunctional team increased by an average of 3% compared to production rates using the Taylor/Ford system (Guimaraes *et al.* 2012).

Based on the literature, little work has been done on either relating motivation theory to learning or the ultimate impact on product variability. The next section discusses the progress to date in conducting initial empirical studies and surveys in industry and draws tentative conclusions of the value of this knowledge to the overall objective of intelligent automation. There is a need to study the relationship between employee motivational factors and learning behaviours in manufacturing process. It is hypothesised that learning by doing different tasks whether they be simple or complex will impact on employee motivational levels as well as increasing job satisfaction and reducing employee turnover.

### **3 RESEARCH METHODS**

#### **3.1 Variability and Task Complexity**

A preliminary pilot case will be conducted in order to determine: what is a complex task, what attributes/constraints make a task complex, what human factors are important and how they vary between operators. The initial hypothesis suggests a high correlation between task complexity and human variability. After a first phase of observation, information collection and Cognitive Task Analysis, a general understanding of task complexity in high-value manufacturing processes will be obtained. Based on this understanding controlled experiments will be designed in order to discover the relationships between task complexity and human variability. A pilot case is being conducted in the laboratory to test the initial hypothesis of the influence of task complexity. The purpose of the pilot study is to analyse three task attributes that are suspected to be responsible for facilitating people to introduce variability, these are: number of required actions to complete the tasks, number of components needed to complete the task, information received in order to complete the task (clarity of instructions, conflict between steps, repetitiveness, change of goals).

This pilot study consists of assembling a LEGO® Mindstorm robot. The pilot experiment will have two phases: In the first phase, the subjects are presented with clear instructions in how to assemble the robot. Future stages of the experiment will ask the subjects to assemble the same model of robot but using deficient instructions. Timing and checking the output comparing with the model, the pilot experiment will be able to show what the personal differences are within the same individual performing the same robot model with full assembling instructions, 70% of the instruction steps and 30% of these steps. The differences (time and final output) among subjects will be also noted. Hopefully this first stage of the pilot experiment will prove that lack of information or unclear instructions for executing a task will lead to variability in cycle time and final product.

The second phase of the pilot experiment will present different LEGO® models to be assembled, increasing the number of components in the models. The experiment tries to prove that the bigger the number components needed to perform a task, the bigger the human variability will be (variations in cycle time and final product). In this case, clear instructions will be presented to all subjects. Initially, the number of components and number of actions are considered to be related, because in this experiment the number of components to be assembled cannot be increased without increasing the number of actions needed in order to complete the task.

Learning curves for subjects have been considered and the effects are expected to be counteracted with the sequence of the experiment, going from easier assembly task to more complex, in the task where subjects are assembling the same model. In this case, complexity is added by reducing the information provided for assembly. In order to minimise the learning curve effect this task has also been programmed with two weeks difference to allow subjects to forget what they learned first time.

If the data collected from the pilot experiment proves that a lack of information and increasing the number of components will lead to higher differences in human performance, this experiment will be tested in actual manufacturing processes. The plan is to start with simpler tasks and then to increase the complexity by adding controllable external factors to observe how individuals respond to stimuli augmentation. Starting with number of components, number of actions and clarity of information, other task factors could be also added to the experiment (dynamic change of inputs, time constraints, more than one acceptable output...). Variability will be measured by means of dimensions, cycle time, missing parts, deficient assembly and any other non-quantifiable attribute considered important from a quality perspective (for instance external appearance). The anticipated outcome from this research is a comprehensive scheme which will help engineers and process designers to understand sources of variability when humans perform complex tasks.

#### **3.2 Motivation and Learning Curve**

Pilot case studies will be conducted at Loughborough University and the Technical University Melaka Malaysia by inviting students and technical staff to participate. A particular aspect of the investigation will focus on the differences in skilled and unskilled students and staff. These findings will be used for the design of real industrial cases studies. Some case studies will be designed to derive the

relationships of variability induced by human operators during tasks and the outcome of the process. The process outcome may be related to the short or long-term implications in terms of the quality of finished products, the impact on learning curves of the employees, etc. Case studies will be conducted in manufacturing by means of digital surveys including multiple-choice and open-ended questionnaires distributed to employees in order to understand the contribution of human operators to variability in manufacturing/assembly operations. Video cameras will be used to capture the capability of skilled and unskilled employees during the process of the manufacture or assembly of products with different complexities. The human resource managers/advisors of the industry will be approached to participate in the study. Respondents will also be asked to complete the hard copy or digital questionnaires that are sent through their email or via their human resources managers/advisors. This survey aims to measure the relationship between the motivational factors and learning behaviours of skilled/unskilled workers in doing the simple/complex tasks as well as the effects on job satisfaction and employee turnover.

#### **4 CONCLUSIONS**

A long-standing problem has been to identify and describe the types of human variability and how they affect manufacturing processes and, reciprocally, how human variability is affected by manufacturing processes. Variability in procedures adopted by the operators may contribute to process variability and hence be transmitted to final outputs. The importance of this research is based on understanding how operators behave when they are dealing with variability from parts and processes in complex manual tasks. It will also identify task characteristics that impede people in adapting to and, to a certain extent, correcting this variability. The initial literature review suggests a high correlation between task complexity and variability. After the completion of the pilot study, a general understanding of some task characteristics and how they affect human performance when executing complex assembly tasks will be obtained. Based on this initial experiment, other experiments will be designed in order to acquire a deeper knowledge about task complexity factors and their influence on the behaviour of humans during real manufacturing processes.

At this stage of the research, it seems that studying task characteristics affecting human performance and proving that some of them negatively influence humans in trying to achieve the desired outcomes may be feasible. The biggest challenge to be faced in this project is to capture how humans adapt to external variability, and in detecting what capabilities (mainly cognitive) are used when performing complex tasks. In addition, extrapolating these findings in specific complex tasks, even if they are actual manufacturing processes, to other manufacturing processes appears risky. It can be claimed that one task characteristic impeding human in reducing part and process variability might not have the same effect in another process.

In addition, the topic of work motivation needs to be explored broadly, as several recent articles have examined how far researchers have come with work motivation, which leads to open questions such as: What is the future work motivation theory? What is the future research agenda? How can we extend or modify the current models so they continue to be relevant in the future? And what are the new model of employee behaviours and job performance in contemporary organizations? These are an example of the challenges for researchers to explore in broader view not only focussing on the work motivation theory but also the relationship between learning behaviours in the workplace. In a very recent study Guimaraes et al. (2012) found that future development should include the learning curve (LC) modelling in training procedures to evaluate their efficiency toward multifunctional and teamwork. The LC modelling will also be used to define an optimal sequence in task rotation aimed at maximizing production levels and worker's satisfaction. It is also suggested by Egan et al. (2004) that future work should include longitudinal studies that measure perceived organizational learning culture, critical incidents and employee motivation, and also comparative studies examining differences and similarities between organizations and relevant outcomes. Further investigation should be made regarding these matters and we should be extremely cautious when presenting conclusions of experiments. The research findings will be incorporated into a methodology to aid the design of automation solutions.

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